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Relative Importance of Conflict Geometry Variables in Influencing Pilots' Conflict Detection Using a Cockpit Display of Traffic Information

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RELATIVE IMPORTANCE OF CONFLICT GEOMETRY VARIABLES IN INFLUENCING PILOTS' CONFLICT DETECTION USING A COCKPIT DISPLAY OF TRAFFIC INFORMATION

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When independent variables are inter-correlated with each other, ANOVAs or traditional multiple regression methods do a poor job for analyzing their relative importance in accounting for the variance in a dependent variable. This paper describes a method called *Dominance Analysis* (Budescu, 1993; Azen & Budescu, 2003) as a better approach than the traditional methods in determining the relative importance of several inter-correlated independent variables in accounting for the variances in pilots' performance measures in a conflict detection task with a cockpit display of traffic information (Xu, Rantanen, & Wickens, 2004). The three variables in question were an intruder aircraft's distance to closest point of approach (CPA) between the pilot's ownship and the intruder aircraft, the intruder aircraft's time to CPA, and relative speed between the two aircraft. Results indicate (1) for absolute miss distance estimate error, distance to CPA was the most important variable than the other two variables; (2) for signed miss distance estimate error, time to CPA and distance to CPA were more important than relative speed; (3) for both absolute and signed time to CPA estimate errors, time to CPA was the most important compared to the other two variables; and (4) for absolute orientation at CPA estimate error, relative speed was the least important variable compared to distance to CPA and time to CPA. Interpretations of the dominance analysis results are offered.

Introduction

Xu, Rantanen, and Wickens (2004) systematically investigated the effects of 2-D air traffic geometry on pilots' conflict detection performance using a cockpit display of traffic information (CDTI). Pilots individually observed the development of conflict scenarios involving their ownship and an intruder aircraft shown on the CDTI (see Figure 1). The ownship and the intruder were flying at the same altitude on straight and converging courses, at constant but not necessarily the same speed. The ownship icon was positioned in the center of the display throughout the whole experiment, appearing stationary to the participant and thus yielding an ownship-centered view of the traffic situation. A conflict scenario was evolving for 15 s, after which the scenario froze. The participant was then required to mentally extrapolate the development of the scenario and press a key when he/she estimated that the closest point of approach (CPA) between the two aircraft was reached (had the scenario not been frozen), thereby providing an estimate of time to CPA. After that, the participant moved the cursor to his/her estimated location of the CPA, thus yielding an estimate of miss distance and orientation at CPA.

Of the independent variables investigated in Xu et al. (2004), the three that were of interest to us for this paper were intruder aircraft's distance and time to CPA from the freezing point and relative speed between the ownship and the intruder. Distance to CPA and relative speed each had three levels (1.33, 2.67, and 4.0 nm for distance; 160, 240, and 480 knots for speed). Because intruder's time to CPA was determined by dividing its distance to CPA by relative speed, an orthogonal manipulation of time to CPA was unnecessary as well as impossible.

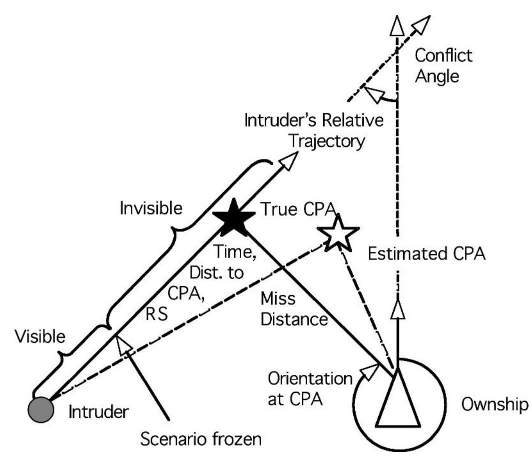

Figure 1. Schematic illustration of key components of the experimental paradigm and independent variables. Adapted from Xu, X., Wickens, C. D., & Rantanen, E. M. (2007). Effects of conflict alerting system reliability and task difficulty on pilots' conflict detection with cockpit display of traffic information. *Ergonomics*, *50*, 112–130, with permission from Taylor & Francis Ltd.

Note that coupling the longest distance to CPA (4.0 nm) with the slowest speed (160 knots) would have resulted in a time to CPA of 90 s and could have resulted in participant impatience. This condition was thus excluded from the experiment, resulting in a total of 5 time to CPA levels (10, 20, 30, 40, and 60 s).

The primary dependent variables were absolute and signed estimate errors of miss distance at CPA and those of time to CPA ("|estimated values – true values|" and "estimated values – true values," respectively). For orientation at CPA, only its absolute estimate error was employed. Absolute errors would reveal the estimation accuracy, whereas signed errors would reveal under- or over-estimation, an indication of directional bias. A main finding of Xu et al. (2004) was that estimation errors increased as relative speed decreased and time and distance to CPA increased. However, because of the interrelationships between time to CPA, distance to CPA, and relative speed, as noted, the effect of one variable as revealed by ANOVAs could well be confounded with the effect of another. For example, in Figure 2, it is not clear whether the effect of distance to CPA on absolute miss distance estimate error was due to distance to CPA itself, or time to CPA, or a combination of these two variables, because a change in the former variable was always associated with a change in the latter variable (controlling for speed). Yet, understanding the relative contributions of the independent variables is critical to correct interpretations of the results.

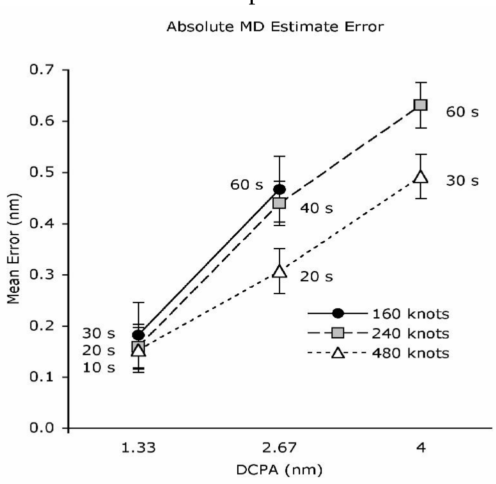

Figure 2. Absolute miss distance (MD) estimate errors by distance to CPA (DCPA), relative speed (in knots), and time to CPA (in s).

Multiple regression is a common tool to examine the relative importance of predictor variables or independent variables that are correlated, and various relative importance measures have been developed such as those based on regression coefficients (e.g., the regression coefficient β_i, associated with predictor X_i), those based on correlation (e.g., simple product-moment correlation, $r_{YXi,}$ or the squared product-moment correlation, $r^2_{YXi,}$ between the criterion and each of the predictors, and squared partial correlation), and those based on a combination of the regression coefficients and the correlations (e.g., the product of the standardized regression coefficient of the predictor and the predictor's correlation with the criterion, $\beta_i r_{YXi}$) (see Azen & Budescu, 2003 for a review). However, according to Azen and Budescu, most of these measures are either correct only in special cases (e.g., r^2_{YXi} is a correct relative importance measure only when predictors are not correlated, but not necessarily so when they are correlated) or lack an intuitive interpretation.

Instead of relying on conventional multiple regression methods, Budescu (1993) and Azen and Budescu (2003) developed a general yet intuitive method of analyzing relative importance of predictor variables, known as dominance analysis (DA), which has been recognized as a better approach and used by many researchers in recent years (e.g., Behson, 2002; Block, 1995; Suh, Diener, Oishi, & Triandis, 1998; Weinberger, 1995). According to Azen and Budescu (2003), relative importance of predictor variables in predicting the criterion variable, *Y*, can be analyzed at three levels, namely, complete dominance, conditional dominance, and general dominance, with decreasing strictness of dominance. Variable X_i is said to completely dominate variable X_j if the additional contribution of X_i to each of the subset models for which the comparison between the two variables is meaningful is greater than that of X_j. Here the additional contribution of a predictor variable to a given regression model is defined as the increase in the proportion of variance in Y accounted for by adding that predictor variable to the regression model. However, complete dominance between two variables cannot be established, if one variable's additional contribution is greater than another's for some, but not all, of the subset models.

To reduce the dominance indeterminacy at the complete dominance level, the second level of dominance, conditional dominance, is based on the average of the additional contributions to all subset models of a given model size, which is the number of predictor variables in a model. For instance, if X_i's average additional contribution for all the model sizes is greater than that of X_j's, then X_i conditionally dominates X_j. As in the case of complete dominance, conditional dominance cannot be established if one variable's average contribution for some but not for all model sizes is greater than another.
The last level of dominance, general dominance, fur-

ther reduces dominance indeterminacy, by taking the overall average of the average values from all the model sizes used for conditional dominance. X_i is said to be generally dominant over X_j, if X_i's overall average conditional contribution is greater than that of X_j.

This paper describes the application of the DA method to the analysis of the relative importance of the three inter-correlated independent variables (distance to CPA, time to CPA, and relative speed) in influencing the performance measures of pilot conflict detection using a CDTI. The DA method has been mostly used for analyzing non-experimental data. However, it should also be an appropriate method for experimental data by specifying fixed rather than random independent variables (personal communications with Razia Azen, September 19, 2005).

Method

In Xu et al. (2004), because of the incomplete factorial design (eight rather than nine conditions resulting from the dropping of the longest distance to CPA/slowest relative speed condition), hypotheses with respect to the effects of distance to CPA, relative speed, , and time to CPA were evaluated with two partly overlapping ANOVAs—(A) on the two shorter distances to CPA and all the three relative speeds, and (B) on all the three distances to CPA at the two faster relative speeds. Similarly, the data for the DA were also split into two partly overlapping sets—(A) and (B) corresponding to the ANOVAs (A) and (B). The DA was conducted separately for (A) and (B) and will be referred to as DA (A) and (B), respectively, and they were expected to reveal similar result patterns. For each of the five dependent variables, the DA was performed at all the three hierarchical levels—complete, conditional, and general dominance. Table 1 shows the correlation matrixes for the three predictor variables: relative speed, distance to CPA, and time to CPA, for DA (A) and (B), respectively.

We were also interested in whether the dominance results obtained could be generalized beyond the particular sample observed from the experiment. The bootstrap procedure was used to accomplish this purpose. The bootstrap is a resampling method which empirically estimates the variance and confidence intervals for a statistic with an unknown theoretical distribution. The core of the bootstrap method is to randomly resample with replacement from the parent sample to generate B bootstrap samples (B is a large number, e.g., 1000), where the size of each sample is equal to the size of the parent sample. Each bootstrap sample, whose observations are similar to but usually not exactly the same as those in the parent sample, can be considered as a random sample of the same population that the parent sample is from. The estimate of the sampling distribution of the statistic in question can then be empirically obtained from the results of the B bootstrap samples (Azen & Budescu, 2003; Efron, 1979; Mooney & Duval, 1993).

Table 1. Sample (n = 48) Correlation Matrices for the Three Predictor Variables: Relative Speed (RS), Distance to CPA (DCPA), and Time to CPA (TCPA)

Analysis	Variable	1. RS	2. DCPA	3. TCPA
A	1. RS	--	.000	-.721**
	2. DCPA	.000	--	.612**
	3. TCPA	-.721**	.612**	--
B	1. RS	--	.000	-.612**
	2. DCPA	.000	--	.750**
	3. TCPA	-.612**	.750**	--

** Correlation is significant at the .01 level (2-tailed).

For multiple regression, different bootstrap processes are used for fixed and random predictors. In this study, although the predictors (or independent variables) were fixed (rather than random), we used random re-sampling bootstrap process. This was justified because using random re-sampling bootstrap has some statistical advantages over fixed re-sampling bootstrap even when the predictors are fixed (Fox, 2002). A detailed report on the bootstrap results is available in Xu, Rantanen, and Huo (2006).

The DA and the bootstrap procedure were performed using a SAS program called Dominance Probability Macro provided by Azen and Budescu (2003) (see Xu et al., 2006 for the SAS codes used for the present study, along with the data).

Results

We first provide examples to illustrate the results of the three DA levels (complete, conditional, and general dominance), followed by a summary of all the results. Table 2 shows the results for absolute miss distance estimate error with relative speed, distance to CPA, and time to CPA as the predictors. The notation R^2 is used to represent the proportion of variance in the criterion variable accounted for by the predictors in a model. In each table, the $2^3 = 8$ models for each of DA (A) and DA (B) and their corresponding R^2 values are shown in the first two columns. The additional contribution of a given predictor is measured by the increase in R^2 when that predictor was added to a regression model. Thus, the additional contributions of relative speed, for example, were computed as the increase in the proportion of variance accounted for when relative speed was added to the subset models of the null subset {.}, {distance to CPA}, {time to CPA}, and {distance to CPA, time to CPA}.

With respect to complete dominance for DA (A) in Table 2, the additional contribution of relative speed to the subset model {time to CPA}, defined as $R^2_{\text{relative speed, time to CPA}} - R^2_{\text{time to CPA}}$, is .0878. This is the difference between the proportion of variance in absolute miss distance estimate error accounted for by both relative speed and time to CPA and the proportion of variance in absolute miss distance estimate error accounted for by time to CPA alone. Because the additional contribution of distance to CPA was larger than that of relative speed to each of the subset models where their additional contributions can be meaningfully compared (i.e., the null subset {.} and {time to CPA}), distance to CPA completely dominated relative speed. As an example to show conditional dominance, the average contribution of relative speed to models of size k =1 was computed as (.0452 + .0878)/2 = .0665. Similarly, the average contribution of distance to CPA to the models of size k = 1 was computed as (.4070 + .1278)/2 = .2674. Because the average contribution of distance to CPA was greater than that of relative speed for each model size (i.e., .4070 > .0452 for k = 0, .2674 > .0665 for k = 1, and .0402 > .0002 for k = 2), distance to CPA conditionally dominated relative speed. Finally, the general dominance measures for relative speed and distance to CPA were computed by averaging all their respective conditional values (i.e., [.0452 + .0665 + .0002]/3 = .0373 for relative speed and [.4070 + .2674 + .0402 = .2382] for distance to CPA). Because distance to CPA's general measure was greater than that of relative speed, distance to CPA is said to generally dominate relative speed.

Below is a summary of the results (the complete set of results are available in Xu et al., 2006). The analyses clearly showed that for each of the criterion variables, the pattern of relative importance of predictor variables was the same at the complete and conditional dominance levels. Furthermore, the DA results at the general dominance level, while reducing the degree of indeterminacy, show a similar but not identical pattern to that at the complete and conditional dominance levels. For absolute miss distance estimate error, across both DA (A) and DA (B) (Table 2), distance to CPA emerged as the most important variable in influencing pilot's estimate error of this most important measure of conflict detection, followed by time to CPA, and relative speed being the least important. The relative importance between distance to CPA and time to CPA is less clear in DA (B) than in DA (A), however.

For signed miss distance estimate error, the relative importance between distance to CPA and time to CPA is ambiguous in that DA (A) shows time to CPA as more important than distance to CPA, but DA (B) suggests a general tendency of distance to CPA's dominance over time to CPA. However, in both DA (A) and DA (B), both time to CPA and distance to CPA were more important than relative speed in accounting for the variance in the dependent variable.

Table 2. Dominance Analysis (DA) for Absolute Miss Distance Estimate Error With Relative Speed (RS), Distance to CPA (DCPA), and Time to CPA (TCPA) as Predictors

DA	Subset model	R^2	Additional contribution of:		
			RS	DCPA	TCPA
A	Null and k = 0 average	0	.0452	.4070	.3366
	RS	.0452		.4070	.3793
	DCPA	.4070	.0452		.0575
	TCPA	.3366	.0878	.1278	
	k = 1 average		.0665	.2674	.2184
	RS, DCPA	.4522			.0125
	RS, TCPA	.4245		.0402	
	DCPA, TCPA	.4644	.0002		
	k = 2 average		.0002	.0402	.0125
	RS, DCPA, TCPA	.4647			
	Overall average		.0373	.2382	.1892
B	Null and k = 0 average	0	.0488	.6240	.5776
	RS	.0488		.6240	.6244
	DCPA	.6240	.0488		.0642
	TCPA	.5776	.0956	.1106	
	k = 1 average		.0722	.3673	.344

				3
RS, DCPA	.6728			.0166
RS, TCPA	.6732		.0162	
DCPA, TCPA	.6882	.0013		
k = 2 average		.0013	.0162	.0166
RS, DCPA, TCPA	.6895			
Overall average		.0408	.3358	.3129

For absolute time to CPA estimate error, it is clear that among the three predictor variables, time to CPA was the most dominant or important in influencing performance, which is true across both DA (A) and DA (B). However, the relative importance between distance to CPA and relative speed is less clear, because the results of the two DAs revealed opposite patterns: dominance of relative speed over distance to CPA in DA (A) and the reverse in DA (B).

For signed time to CPA estimate error, across both DA (A) and DA (B), time to CPA was the most important factor in influencing its variance. The relative importance between distance to CPA and relative speed is somewhat less clear, because in both DA (A) and DA (B) their relative importance cannot be established at the complete and conditional dominance levels, although at the general dominance level relative speed was more important than distance to CPA. This result is somewhat inconsistent with the distance-over-speed bias as evident in the ANOVA performed in Xu et al. (2004), which suggests the dominance of distance over speed. This difference may be attributable to the fact that the analysis for the distance-over-speed bias considered only a subset of data comparing the pairs of conditions with equal times to CPA, whereas the DA method included the data of all the conditions.

Finally, for absolute orientation at CPA estimate error, the relative importance between distance to CPA and time to CPA revealed by DA (A) is the opposite of that by DA (B), so no clear conclusion can be drawn. However, in both DA (A) and (B), relative speed was the least important factor.

Based on the above results, we offer with reasonable confidence the following conclusions regarding the relative importance of the three independent or predictor variables in predicting or influencing pilots' conflict detection performance: (1) for absolute miss distance estimate error, distance to CPA was the most important variable, (2) for signed miss distance estimate error, time to CPA and distance to CPA were more important than relative speed (i.e., relative speed is the least important), (3) for both absolute and signed time to CPA estimate errors, time to CPA was the most important, and (4) for absolute orientation at CPA estimate error, relative speed was the least important variable compared to distance to CPA and time to CPA. Note that where no conclusion with respect to the relative importance between two predictable variables was made, it was mainly because of the ambiguity resulting from opposite results of DA (A) and DA (B) (i.e., one variable was more important than another as revealed in one and the opposite in the other).

Discussion

From the standpoint of experimental design, independent variables should be orthogonally manipulated. However, the nature of the relationship between distance, speed, and time made it inevitable that the three independent variables that were the focus of this study were inter-correlated. As noted, ANOVAs and the traditional multiple regression methods in general are not adequate for tearing apart the relative contributions of independent variables when they are tangled with each other. The DA method seems to offer a viable and better alternative. Although the ANOVA results in Xu et al. (2004) showed that distance to CPA, time to CPA, and relative speed all had some effects on the performance measures, the DA results suggest that their relative influence on conflict detection performance varied across different measures.

Distance to CPA was a more important factor than time to CPA and relative speed in influencing absolute miss distance estimation error. One interpretation of this result is that when the intruder's distance to CPA was long, faster speed of the intruder (and the shorter time to CPA) was not going to increase the estimation accuracy of miss distance too much; instead, it was largely determined by the distance to CPA. Since miss distance was derived from the location of the CPA, whatever influenced the estimate accuracy of CPA location would also influence the miss distance estimate accuracy. A conceivable method for the pilot participant to estimate the CPA location was to estimate the interception point between the future trajectory of the intruder icon and a line connecting this trajectory and the ownship icon forming a right angle (90°), both of which themselves needed to be extrapolated (see Figure 1). The estimate error of CPA location (and therefore miss distance estimate error) was subject to the angular extrapolation errors of a) the line linking the intruder's extrapolated trajectory and the ownship icon at 90°, and b) the intruder's extrapolated trajectory. The latter angular error was presumably amplified at greater distance to CPA. Although relative speed (perceived while the intruder icon was visible) and time to CPA might also have affected the stability of this angular estimate, they were apparently not as influential as distance to CPA. By the similar mechanism, distance to CPA was more influential than relative speed when it comes to the estimation of orientation at CPA, because orientation at CPA was also derived from the CPA location.

In contrast, the effect of the true time to CPA was more pronounced than that of distance to CPA and relative speed on time to CPA estimation. One interpretation of this is that even when the two aircraft were very close in distance, if their relative speed was very slow (thus time to CPA was long), pilots might not be able to estimate the time to CPA accurately. This finding is consistent with Peterken, Brown, and Bowman (1991), who showed that it was the time rather than the distance during which a moving object was not visible that was the more important factor in influencing the time-to-contact estimation accuracy.

Conclusions

Pilot performance in conflict detection using sophisticated cockpit systems (e.g., CDTI) is of critical importance to the modernization of air traffic management systems and advancing the concept of free flight. Interrelationships and interactions of many of the multitude of factors affecting the performance complicate both the design of experiments as well as analysis of the data, as exemplified by our investigation of distance and time to CPA and relative speed of the aircraft involved in a potential conflict. Because of such complexities, proper choice of the tools for analysis warrants careful consideration. Our research showed how traditional methods may not be able to discern important patterns in the data, and how alternative techniques allow for drawing significant conclusions from complex experimental designs examining complex phenomena. Our results not only shed more light on how pilots performed a conflict detection using a CDTI, but also provide insights into the cognitive mechanisms of motion perception especially estimation of CPA and time-to-contact. Finally, pilot training may benefit from our findings; pilots should be aware of what geometry factors influence conflict detection and which factors make it more challenging.

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